Explore what-if scenarios with SONG: Social Network Write Generator

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Abstract

Online Social Networks (OSNs) have witnessed a tremendous growth the last few years, becoming a platform for online users to communicate, exchange content and even find employment. The emergence of OSNs has attracted researchers and analysts and much data-driven research has been conducted. However, collecting data-sets is non-trivial and sometimes it is difficult for data-sets to be shared between researchers. The main contribution of this paper is a framework called SONG (Social Network Write Generator) to generate synthetic traces of write activity on OSNs. We build our framework based on a characterization study of a large Twitter data-set and identifying the important factors that need to be accounted for. We show how one can generate traces with SONG and validate it by comparing against real data. We discuss how one can extend and use SONG to explore different 'what-if' scenarios. We build a Twitter clone using 16 machines and Cassandra. We then show by example the usefulness of SONG by stress-testing our implementation. We hope that SONG is used by researchers and analysts for their own work that involves write activity.

Keywords: Online Social Networks, Activity modeling, Twitter, Facebook

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1. Introduction

OSNs have increased in popularity the last few years and they attract hundreds of millions of users. OSNs differ from traditional web applications in atleast two respects: they serve highly personalized content and have to deal with non-traditional workloads [3, 27].

Complimenting this rise of popularity has been the vast amount of research done on OSNs – from analyzing social communities[18, 15, 2], to studying presence of social cascades in OSNs [3, 33, 10, 4, 5] and solving problems of large scale OSNs [24]. Most of this work is aided by real datasets collected by elaborate crawls on OSNs. However gathering datasets is hard for multiple reasons - some OSNs like Facebook have high privacy settings making it hard to obtain a proper sample. OSNs like Twitter have caps on the number of API calls that can be made[1], making a large crawl a long and elaborate affair. And sometimes, data that has been collected cannot be released due to legal reasons [6]. Lack of data inhibit researchers and analysts to properly conduct research. In addition, even when a sample is collected, the sample only captures characteristics present at the time of collection, limiting the scope of using the sample.

The main contribution of this paper is SONG - a framework to generate synthetic and realistic traces of write activity of users in OSNs. We focus on modeling writes as from a system perspective, writes have more impact than reads (issues of consistency etc.) and a read is performed whever a write event occurs. In order to generate synthetic traces, we treat the problem of generating writes as a classical time-series modeling problem of a count process, with the number of writes in given time interval representing counts. We build a model of write activity of users that can span long time scales - days as well as short time scales - seconds. In cases where researchers and analysts have no data, they can use SONG to generate traces that are realistic. And in cases where some datasets are available, researchers and analysts can use SONG to estimate parameters from the existing datasets, and generate new traces to explore different *what-if*

[1] http://apiwiki.twitter.com/Rate-limiting

scenarios, including forecasting, benchmarking, capacity planning, performance analysis and effects of flash crowds.

In order to understand what factors effect write activity and hence are necessary to consider in any framework in order to generate realistic traces, we characterize different user-centric properties of data collected by a large crawl of Twitter along with associated writes (in the form of tweets) [25]. We confirm some findings that have been reported before – the presence of diurnal trends [10], a small subset of users have high activity; the activity of users follows a skewed distribution and geographical properties of users; most users are from the US[14]. We also report new ones – to the best of our knowledge, inter-write activity of users is distributed log-normally in time, a finding that is closer to observed online behavior of humans [28]. We also observe writes do not show self-similar behavior.

SONG is based on two components - the first component is responsible for modeling and generating time-varying trends that operate at longer time scales (diurnal variations). The second component is responsible for modeling activity at short time-scales (seconds - a couple of hours). The model we pick is simple, intuitive and fits our purpose. We provide guidelines to generate traces when no data-sets are available using standard off-the-shelf methods. When data is available, we show how one can estimate different parameters that are used by SONG. We validate SONG using real data and show that traces generated by SONG match real data closely.

As statistician G.E. Box put it: "All models are wrong, some models are useful". To show the efficacy of SONG on a real system, we implement a clone of Twitter using Cassandra [9] on 16 commodity machines. We validate the trace generated by SONG against the real data set, by monitoring system-specific metrics like CPU activity, IO activity and network traffic produced in the back-end. We then show by example the usefulness of SONG - by considering a simple yet crucial scenario - benchmarking the system and uncovering bottlenecks.

2. Related Work

The main contribution of this paper is a framework for generating time-series of activities (writes) of users in OSNs. Towards this end, we build up on various concepts from previous work done in this area. We compare and contrast our work with related work in this section.

Much work has been done on characterizing and understanding information propagation in social networks [5, 4, 21, 13, 12]. However, most of this work deals with the spread of *content* (in an OSN like Flickr [5, 4]) and what factors are responsible for information cascades to form. Our work is different as we deal with modeling of user activity over time; writes in an OSN and how such a model can be useful. In addition, we focus on modeling an aggregate of users, instead of focusing on individual users or a specific community of users.

The closest to our work is the work on understanding user interactions in OSNs [33, 10, 30, 31, 6]. The authors of [33] use a crawl of Facebook to extract a social-interaction graph and show that such a graph deviates from the social graph and how these differences can manifest themselves in gauging the performance of social applications running on these graphs. A similar message was delivered by the authors of [30] where they advocate using a more 'dynamic' view of the social graph, rather than a static friendship graph for analysis. The authors of [10] investigate the posting behavior of users in OSNs and show that users exhibit strong diurnal patterns, something we observe as well in our datasets. In addition the authors show that the posting behavior follows a stretched-exponential distribution. In our datasets, we see that user posting behavior (tweets) follows a log-normal distribution and is more in line with human response dynamics [28]. We use these properties while building our model. Finally the authors of [31] study the evolution of social links over time, by studying user interaction.

Our work can be seen as complementing recent work on characterizing user workloads on OSNs by analyzing clickstream data [3, 27]. These works primarily focus on studying the impact of OSNs on the network, by studying how users interact with different OSNs. Our work is markedly different as we fo-

cus on modeling interactions in an OSN and we believe that our model can be incorporated in a more comprehensive model of user behavior.

Finally, we use data gleaned from the Twitter network for our work, and we find similar behavior as has been observed [14, 16]. To the best of our knowledge, this is the first work dealing with modeling of interactions (writes) in an OSN with the hope that researchers and analysts alike can use the model to generate synthetic traces for their own work.

3. Data

Our dataset consists of a crawl of Twitter [14] conducted between Nov 25 - Dec 4, 2008. The social graph that we crawled has $2,408,534$ nodes and $38,381,566$ edges (although Twitter has directed edges, we report total edges and use edges as undirected unless otherwise stated). The crawl was done by a standard BFS.

We also collected traffic on Twitter in the form of 'tweets' (total 12M tweets) generated by the 2.4M users by using the Twitter API[2]. From the tweets, we mined the following relevant fields: *tweet_id*, *timestamp*, *user_id*, *location* and *content*. This information allows us to get traffic information for every user and how this traffic is distributed across users. Approximately 25% of the population (587K) generated at least one tweet, for the rest of the users the Twitter API did not return tweets in the 19-days period under examination. Given the broadcast nature of Twitter (a tweet is sent to all the followers of a user), the 12M tweets lead to an excess of 1.7B messages actually traversing the system. An initial study of our data (and borrowing the terminology used in [14]) revealed the presence of *broadcasters* - users or automatic programs (like 'cnnbrk') that publish tweets at high frequency and normally have many followers as well as *miscreants* or spammers who also publish tweets at a high rate but have few or no followers. As we are interested in modeling legitimate users, we filter out these spammers by using a simple method - all users who

[2]http://apiwiki.twitter.com

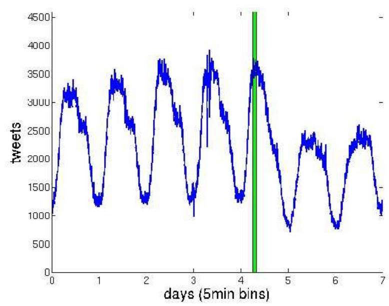
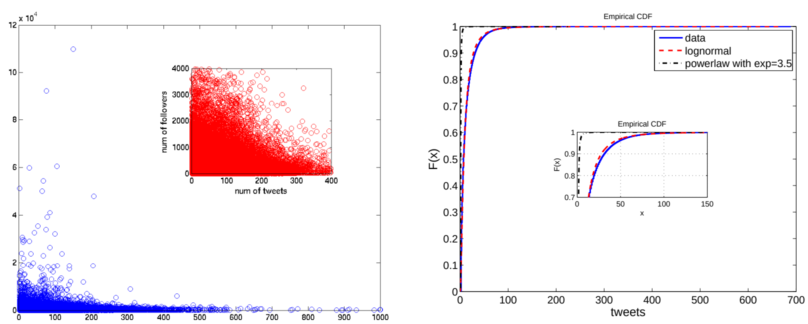


Figure 1: Tweets for 1 week, 5 minute bins

have more than 80% of the maximum number of tweets (during the 19 days) and have less than the median number of followers are filtered. In our dataset, the maximum number of tweets by a single user was 1000, with mean and median number of tweets per user being 21.2 and 8 respectively, with the standard deviation being 35.08. The median number of followers is 8, the mean is approx. 64. We therefore classified all users who have more than 800 tweets and less than 8 followers as spammers and removed them. A manual inspection revealed all high-rate spammers were removed. It is possible low-rate spammers are present in the dataset, but they do not skew our modeling process. In addition, we also removed users who tweet only once during the 19 day period. We ended up with 346424 users. There exist larger data-sets of Twitter [16], however the traffic information collected is different (traffic pertaining to trending topics) and does not consist of the tweets of individual users. To the best of our knowledge, this is the largest dataset with user activity (tweets). In this paper, we present results from 1 week (shown in Fig. 1). For further evaluation, we also consider a trace of 2 hours labeled as the 'busy-hour' trace where the mean and variance are fairly stable. (highlighted in green).

Limitations with the data: While we are aware that unbiased sampling methods like Metropolized sampling method (MRW) exist [29], the size of our dataset when collected suggest that a large portion of the social graph was captured. When we collected the tweets of individual users, we noticed tweet ids were non-contiguous. This implies the API missed returning some tweets.



(a) (b)

Figure 2: (a) Number of followers vs writes, (b) CDF of writes per users

A cursory look at the id distribution in our dataset reveals the API could have lost upto 60% of the tweets (although uniformly distributed), however, we do not have additional information to confirm this number.

4. Characterization

In order to develop a framework to generate synthetic traces that are realistic, we need to first understand what facets of data are important enough to consider. In addition, if we want the framework to be beyond merely curve-fitting; descriptive, we need to consider processes that are generative. For this, we study properties of the dataset we collected to guide our design.

4.1. User Properties

Diurnal Properties: From Fig. 1, we see that users follow a strong diurnal pattern with respect to writing (tweeting) and the number of writes are bursty, and is similar to traffic patterns observed in IP networks. We need to account for this trend in SONG.

Correlation between degree and rates: Do users write more because they are high-degree nodes or are they high degree nodes because they write more? To answer this question, we first plot the number of followers against the number of writes for each user in Fig. 2 (a) and we note there is little or no discernible correlation (a similar observation has been reported before [16]). We observed the same when we plotted number of writes against the number

of friends. This could be the artifact of the system we consider - Twitter, that lets users follow or be followed without an explicit social relationship. For our purposes we do not consider incorporating the degree of a user (number of followers/friends) in our model explicitly, although we show later how SONG can be extended to incorporate this.

Distribution of activity between users: Not surprisingly, users show high variance when it comes to the number of writes they generate (also observed in [16]) (Fig. 2 (b)). We try fitting the distribution with a power-law ($p(x) \propto x^{-\alpha}$, using the method described in [7]) and a log-normal distribution ($p(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}$) and we note an excellent fit with the log-normal distribution (parameters 2.05, 0.9921). We note that a power-law is more appealing as it is more parsimonious, but we do not see a good fit. How does this distribution arise? We know that log-normal distributions arise by multiplicative processes [20], however to fully characterize this underlying multiplicative process is beyond the scope of this current paper. We incorporate distribution of activity in SONG.

Inter-write distribution for individual users: An important property to understand is when do individual users write; the inter-write distribution of users. For this, we focused on the top 10000 users in terms of the number of tweets and found the best fit for the inter-write distribution is the log-normal distribution, which is closer to what has been reported for email communication [28] etc. The Kolmogorov-Smirnov test on the log-normal fits yielded a positive result for 98.1% of the users, while it was 32% for the fits with the exponential distribution. However we make a conscious decision to model aggregate of users, and the aggregate inter-write distribution follows an exponential distribution [1].

Geographical Properties: To construct a framework from *first-principles* where different parameters of a model have a physical interpretation, using geography as input to a model is highly appealing [19, 14]. After basic preprocessing of our data we obtained 187K different locations for the 996K users where the location text was meaningful. After filtering, we obtained standardized locations for 691K users. Of these users, 60.2% belong to the US with UK coming a

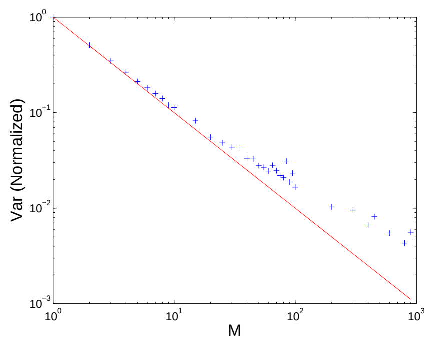


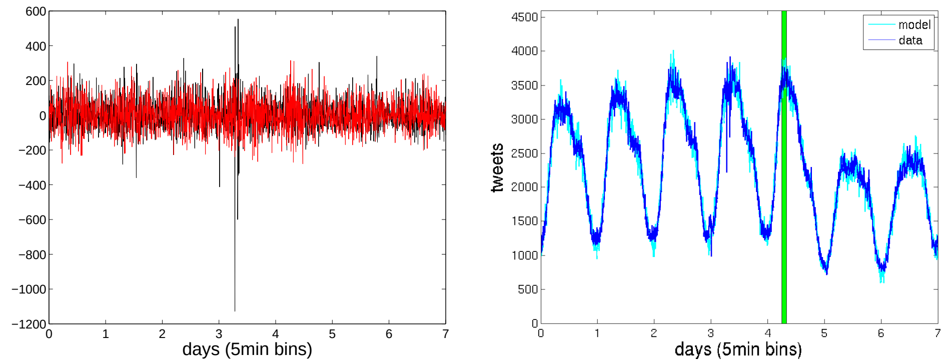
Figure 3: Variance time plot for busy hour (2hr)

distant second with 6.2% of the nodes. Of the users we consider (346K), around 82% of them belong to the US. As we do not have sufficient information, we do not consider geography or locality properties in our framework and leave it for future work.

4.2. Statistical Properties

Test for independence in arrivals: OSNs are known to experience information cascades, where content becomes popular by word of mouth and gets propagated on social links [4, 5]. This would imply that independence of arrivals (at smaller time scales) does not hold. A generic test for independence in write arrivals is autocorrelation – low values at different lags signify little or no correlation. The autocorrelation value steeply decreases for our set of arrivals, with lag=1 having a low value of 0.11 - implying statistical independence. This can be explained as we work at an aggregated level (aggregated over all users), and correlations can be washed out.

Test for self-similarity in write counts: Self-similar behavior in the time series of writes implies that there is no 'natural' length for a burst of writes; the bursts appear on a wide range of time scales. From an engineering perspective, self-similar behavior in traffic can have a profound impact on the design, control and analysis of such systems. A lot of work has been in observing self-similar behavior in IP networks [17, 23], modeling [23] as well as performance analysis with self-similar traffic [8]. It is important to account for self-similar behavior



(a) (b)

Figure 4: (a) Noise model, (b) Model vs Data

in a model, if it is present. A simple visual test for self-similar behavior is the variance-time plot. If we define $X = (X_t : t = 0, 1, 2..)$ to be a stochastic process that represents the time-series we deal with, then we can create a new time-series $X^{(m)}$ for each $m = 1, 2, 3..$ by averaging the original series X over non-overlapping blocks of size m. For self-similar processes, the variances of aggregated process $X^{(m)}(m = 1, 2, 3..)$ decrease linearly in log-log plots with respect to increasing m with slopes arbitrarily flatter than -1. However, for normal processes, this slope is close to -1 [23]. Strictly speaking, a rigorous analysis of the presence/absence of self-similar behavior needs datasets that span more time-scales, we don't have such data-sets. However, we still consider the 'busy-hour' trace (as it displays stationarity) and plot the variance-time plot (with aggregated variance over 3 orders of magnitude) in Fig. 3. We note that the slope is close to -1, showing a lack of self-similar behavior.

In this section, we have tried to enumerate properties of data that a framework has to consider. In the next section, we describe our framework SONG that build up on what we learned in this section.

5. Framework and Trace-Driven Evaluation

In this section, we first describe the model that forms the basis of SONG to generate synthetic traces. We then evaluate the framework by using our

datasets.

5.1. SONG - Methodology

Let $X_i(t)$ denote the number of writes produced by user i, $1 \leq i \leq N$ with N the total number of users at a time instant t, where $X(t) = \sum_{\forall i} X_i(t)$. The time can vary from seconds to weeks, we focus on one week for modeling purposes, with the basic unit being 1 sec. The description $X(t), \forall t$ gives the time series aggregated over all users. We start with the observation that we need to account for two different time-scales - the first time scale spans multiple hours or days and we note the presence of diurnal trends (from Sec. 4.1). The second time scale spans seconds to a couple of hours where the mean and the variance are fairly stable. For the first time scale, we can have a model for the mean m_t of the time series that varies with time in a predictable way. For the second time scale, we can have a stochastic component. The model then is

$$X(t) = m_t + \sqrt{am_t}W_t \tag{1}$$

where m_t is function of time and W_t is a stochastic component which can be a zero-mean, finite variance process and a is a parameter called 'peakedness' (with the same units as $X(t)$) that accounts for magnitude of fluctuations. This model has been used before for modeling backbone traffic in IP networks with success [26], and is appealing to use in our context for the following reasons: it[3] accounts for diurnal variations as well as short time scales, allows for using an infinite variance process like Fractional Gaussian Noise (FGN) to account for self-similar behavior [22] or a finite variance process, what we note in our data. The model is also intuitively appealing as it captures the effect of multiplexing many sources, in this case, users. We now describe how to model different parameters and generate traces.

Modeling m_t: In order to model the time varying mean, we can use a set of basis functions (Fourier, wavelet or principal components) that capture the main

[3] We abuse the notation here as the original model was intended to model a continuous count process, we are using it to model a discrete process.

Methodology	Empirical Data	Off-the-shelf
1. Generate m_t	Use Fourier/wavelet transforms and select appropriate number of coefficients	Generate and select basis functions to represent diurnal variations
2. Generate W_t	Use WGN/FGN by estimating parameters from data	Use WGN/FGN with self-selected parameters
3. Pick a	Estimate from data	Pick a suitable value
4. Generate time series of interactions and assign users to interactions	Use suitable distribution from data	Use a suitable distribution

Table 1: Methodology to generate synthetic traces

frequency components of the data. Ideally, one would associate the presence of different frequencies in the diurnal trend to factors like geography (users in different time zones becoming active during different times), however a detailed characterization of this is not possible as we lack the data. We do however have the following facts to guide us. First of all, the mean of the time series can be fixed. This is related to the number of users in the OSN. Then we can generate time-varying waves (like sinusoids) with a given amplitude and frequency - for instance the largest amplitude wave normally has a periodicity of 24Hrs. The next largest waveform has a periodicity of 12Hrs etc. A linear combination of these waves can form realistic diurnal patterns. If data is available, then one can directly use a time decomposition method of choice (Fourier, wavelets etc) and pick the adequate the number of components.

Modeling W_t, a : W_t can either be a zero mean, finite variance process (like white gaussian noise) or a process with infinite variance (like FGN). Once we decide on W_t, we need to fix a. As described earlier a represents intuitively

refers to how the unit variance (from W_t) should scale at a given time t. For higher values of variance, a higher value of a should be given and vice versa. If we have data, we can estimate $\hat{a}$ as $Var(z_t)$, where $z_t = \frac{X(t)-\hat{m}_t}{\sqrt{\hat{m}_t}}$, given we have $\hat{m}_t$ from the step above and x_t is the data.

Generating Traces: We can use Eqn. 1 to generate the time series of interactions, but we still have to assign these to actual users. We can use a distribution that characterizes the number of interactions per user and can perform inverse sampling [4] to assign interactions to users. This distribution can factor in degree distribution (if there is correlation between degree of a user in a social graph and the number of interactions the user produces), or use distribution weighted by the pagerank of users (as shown recently in [16] to be important). The entire methodology is presented in Table 1.

5.2. Validating SONG with real data

In order to validate SONG with real data, we proceed as follows. We pick the data from *previous* week. We use the Fourier series to represent the time series. After performing the fourier decomposition, we note that the top 10 coefficients account for 81% of the total variance. We therefore use only these 10 coefficients and generate a the diurnal trends $\hat{m}_t$. Note that the first component is the mean of the time series.

In order to choose an appropriate noise model for W_t, we go back to our data and extract the residual noise by subtracting $\hat{m}_t$ from the data of the week in consideration. The residual noise is shown (in black) in Fig. 4 (a). Visual inspection as well as further study using the QQplot and the Anderson-Darling(AD) test reveals the noise to be close to a normal distribution. Hence we use a zero-mean, and a unit variance process for W_t. We estimate $\hat{a}$ to obtain $\hat{a} = 3.4$. In the small dataset we have (19 days), the value of $\hat{a}$ is stable, although we need more data to establish any property. When we regenerate the noise process (second term of Eqn. 1) using a zero mean, unit variance W_t, the

[4] http://en.wikipedia.org/wiki/Inverse_transform_sampling

estimated $\hat{a}, \hat{m}_t$, we get a close match (in red) as can be seen in Fig. 4 (a). We then generate the time-series of writes using Eqn. 1.

From Sec. 4.1, we learnt that the tweet counts per user follow a log-normal distribution. We therefore use this distribution to assign tweets to users. The result is presented in Fig. 4 (b), and we note a close fit to real data, reproducing long-term trends (dirunal trends) as well as short term trends.

Limitations of SONG: One possible route to build a framework is to model behavior of individual users in the social network, generate interactions of each user, and then aggregate these interactions. This is an appealing option as one can directly consider user-centric phenomena like information cascades as well as dynamics of interactions between users [31]. This however, has the problem of making a model much more complex, with more parameters to be considered. We chose to work at a level where users are aggregated and have a much simpler model for our purpose. At present, we don't account for cascades explicitly and this is left for future work.

Although SONG is a fairly general and flexible framework, our evaluation has been done based on a dataset from Twitter - a pub-sub system and some of the results presented may not extend to other popular OSNs like Facebook, Orkut etc. However, we argue that even for other OSNs, the write activity is broadcasted to one's neighbors (e.g. wall postings, 'I likes' in Facebook), and would tend to follow similar patterns. We focus solely on write patterns in OSNs as obtaining read patterns is near impossible by crawls. If read activity is closely correlated to write activity, then we can produce reads as well.

5.3. What-if scenarios with SONG

We present three scenarios where SONG can be useful.

Forecasting/Capacity Planning: Consider the scenario where the user base of an OSN doubles overnight, leading to an increase in interaction rate. This can be easily modeled by varying m_t in the model, generating traces and studying them. Some OSN architectures use message queues [11], that can be modeled as a network of queues and the performance of the system can

be gauged under different scenarios using trace-driven simulations using traces generated by SONG.

Traffic Analysis: OSNs can face 'anomalous' events like flash crowds and high trending topics (like 'Michael Jackson' etc.) [16] that change the profile of traffic. In order to study such phenomenon, one can generate 'normal' traffic using SONG to compare or use SONG to generate traffic with such events. A simple extension to the model we use in Eqn 1 is: $X(t) = m_t + \sqrt{am_t}W_t + I_t$ where I_t is an indicator function and can be used to inject high traffic at different time intervals to mimic flash-crowds or high loads. This can be used for benchmarking as well.

Rise of popularity of OSNs in different geographical areas: Consider the case where an OSN is currently popular in the US and suddenly becomes popular in a European country. This popularity manifests itself as an increase in the number of interactions from a certain geographic area of the world, with a different temporal profile. This can be handled by producing traces for one time-zone, time-shifting this set of traces to produce a new set and aggregating the two.

6. Exploring what-if scenarios

In previous section, we described our framework SONG in full detail, validated the framework with real data, discussed the limitations and briefly discussed some scenarios where SONG can be used. In order to show the effectiveness of SONG for testing real systems, we implement a Twitter-like system and test this system against different traces generated by SONG.

6.1. Our OSN Implementation

We implement a toy OSN that emulates most of the functionality of Twitter. In our system, each user can *follow* other users by creating explicit links. Each user can update *status* and can read the last 20 *status updates* of all the *one-hop* neighbors of the user. The back-end of our toy OSN system is implemented using Cassandra (ver 0.5.0) key-value datastore, with default settings and over

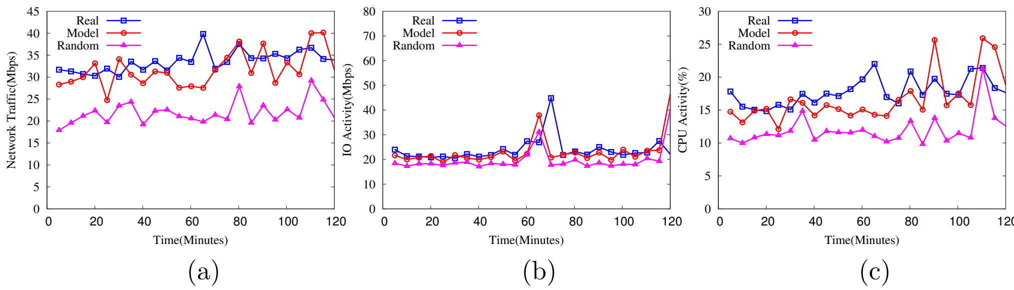


Figure 5: (a) Network traffic, (b) I/O activity, (c) CPU activity

16 machines connected by a 1G Ethernet switch. Each machine is a Pentium Dual Core 2.33Ghz, 2GB of memory and 80GB of disk and run Ubuntu 8.04. The layout of how data is stored in our back-end is based on [32].

We load the social graph described in Sec. 3 into our system. For all the experiments, we use a dummy front-end python client that connects with Cassandra back-end through Thrift API. The front-end client parses the traces and directs requests to back-end by performing Cassandra API calls. We use *iostat* tool to monitor CPU and IO activity. For network traffic, we read */proc/net/dev/eth1* to access different counters of the network interface.

6.2. Validating the Model

We first validate the model by generating realistic trace using SONG (using estimated parameters) of the busy-hour and comparing system parameters - network traffic in the back-end , I/O activity and CPU activity against that of real data. In addition, we also compare against a trace that resembles the data in a temporal sense, but the writes (tweets) are assigned uniformly at random to users – which is common practice.

Fig. 5 shows the system activity with the 3 traces (each datapoint represents mean across 5 min bins). The random trace under-estimates the load across all the system parameters that we measured. In case of network traffic, the average traffic load is 36% lower than the real trace. This result underscores the usefulness of using SONG to generate realistic traces. In contrast to the

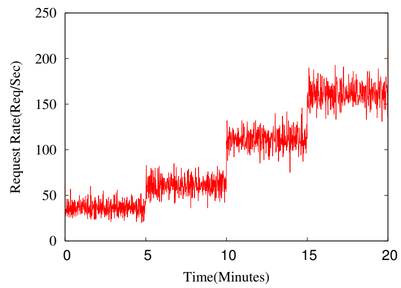


Figure 6: Tweets per seconds

random model, the match between our trace and the real trace is much higher. For instance, the average network traffic only differ by 6% among 2 traces. We like to note here that quantitative results are insignificant here, as one can tune Cassandra to optimize performance. We are more interested in *qualitative* results.

6.3. Benchmarking - Stress Test

The next scenario we consider is a common task carried out by sysadmins - to benchmark the system and uncover the bottlenecks. One can do this by using benchmarking tools that are oblivious of the characteristics of application-specific workloads. However as we showed in the previous section, using a trace with some grounding to reality can give more accurate results and can thus identify bottlenecks with higher confidence.

The typical steps followed for benchmarking include - generating a set of traces with increasing resource requirements, running the system with these different traces and monitor the QoS. Given a minimal target QoS, we can then determine the maximum workload that can be supported by the system infrastructure.

We use SONG to generate traces by increasing the number of writes every 5 minutes from 25 writes/sec to 150 writes/sec (adding to existing writes, while keeping the variance and the overall write distribution across users the same as real data), using the extension discussed in Sec. 5.3. Fig. 6 shows the write rate for 20 minutes in our test. We monitor the response time of every operation

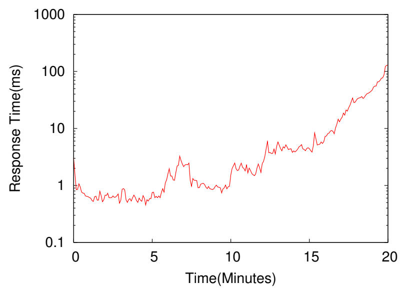
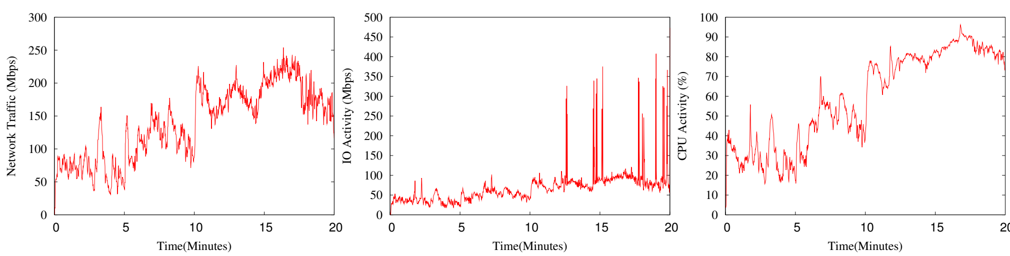


Figure 7: Response time across time



(a) (b) (c)

Figure 8: (a) Network traffic, (b) I/O activity and (c) CPU activity

(get/put) of Cassandra from the front-end[5]. Fig. 7 show the average response time, in bins of 5 seconds. Notice that y-axis is in log scale. Despite variance in the response time, we observe that our Cassandra cluster is able to handle all the requests in less than 10 seconds, up to 100 writes/s. When the request rate is about 150, our cluster collapses and the response time raise sharply up to more than 100 ms.

Fig. 8 shows the activity in back-end network, I/O and the CPU utilization. We observe that although the total network traffic goes up to 250Mbps, we have a 1G switch, so network is clearly not the bottleneck. We then checked the disk activity and it is only 40% of the disk capacity. So we can conclude that CPU is our bottleneck that saturates the entire system when the load increases more

[5]Notice that the number of required Cassandra operations per new write depends to the number of followers of the user.

than 100 tweets per second - as can be seen in Fig. 8 (c). We'd like to reiterate again that this exercise is to show the usefulness and the versatility of SONG, as opposed to uncover particular system issues with Cassandra. Hence the results should be interpreted qualitatively.

7. Conclusions

In order to conduct research in the increasingly popular area of OSNs, we need data-sets. However, data-sets may be hard to get for a number of reasons. The main contribution of this paper is SONG - a framework for generating synthetic and realistic traces of writes of users in OSNs. In order to develop the SONG framework, we characterized a large trace of write activity from Twitter. We then developed the framework and showed how it can be used when prior traces are available or when no traces are available. In order to show the effectiveness of SONG, we evaluated traces generated by SONG using a real system implementation of a Twitter clone and showed by example the utility and versatility of SONG. We intend to release code for SONG in the near future and hope it can be used by researchers and analysts to generate traces to study different 'what-if' scenarios.

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References

[1] Albin, S. L. On Poisson Approximations for Superposition Arrival Processes in Queues. *MANAGEMENT SCIENCE 28*, 2 (1982), 126–137.

[2] Backstrom, L., Huttenlocher, D., Kleinberg, J., and Lan, X. Group formation in large social networks: membership, growth, and evolution. In *Proc of ACM KDD '06*.

[3] Benevenuto, F., Rodrigues, T., Cha, M., and Almeida, V. Characterizing user behavior in online social networks. In *Proc of ACM IMC '09*.

[4] Cha, M., Mislove, A., Adams, B., and Gummadi, K. P. Characterizing social cascades in flickr. In *Proceedings of the 1st ACM SIGCOMM WOSN'08*.

[5] Cha, M., Mislove, A., and Gummadi, K. P. A measurement-driven analysis of information propagation in the flickr social network. In *Proc. of WWW'09)*.

[6] Chun, H., Kwak, H., Eom, Y.-H., Ahn, Y.-Y., Moon, S., and Jeong, H. Comparison of online social relations in volume vs interaction: a case study of cyworld. In *Proc. of ACM IMC '08*.

[7] Clauset, A., Shalizi, C. R., and Newman, M. E. J. Power-law distributions in empirical data. *SIAM Review 51* (2009), 661.

[8] Erramilli, A., Narayan, O., and Willinger, W. Experimental queueing analysis with long-range dependent packet traffic. *IEEE/ACM Trans. Netw. 4*, 2 (1996), 209–223.

[9] Facebook. Cassandra. http://www.facebook.com/ note.php?note_id=24413138919.

[10] Guo, L., Tan, E., Chen, S., Zhang, X., and Zhao, Y. E. Analyzing patterns of user content generation in online social networks. In *Proc of ACM KDD '09*.

[11] highscalability.com. Twitter architecture. http://highscalability.com/scaling-twitter-making-twitter-10000-percent-faster.

[12] Kempe, D., Kleinberg, J., and Tardos, E. Maximizing the spread of influence through a social network. In *Proc. of ACM KDD '03* (2003).

[13] Kossinets, G., Kleinberg, J., and Watts, D. The structure of information pathways in a social communication network. In *Proc. of ACM KDD '08* (2008).

[14] Krishnamurthy, B., Gill, P., and Arlitt, M. A few chirps about twitter. In *WOSP '08: Proceedings of the first workshop on Online social networks* (New York, NY, USA, 2008), ACM, pp. 19–24.

[15] Kwak, H., Choi, Y., Eom, Y.-H., Jeong, H., and Moon, S. Mining communities in networks: a solution for consistency and its evaluation. In *Proc. of ACM IMC '09*.

[16] Kwak, H., Lee, C., Park, H., and Moon, S. What is twitter, a social network or a news media? *Proc. of WWW 2010 (to appear)* (2010).

[17] Leland, W. E., Taqqu, M. S., Willinger, W., and Wilson, D. V. On the self-similar nature of ethernet traffic (extended version). *IEEE/ACM Trans. Netw. 2*, 1 (1994).

[18] Leskovec, J., Lang, K. J., Dasgupta, A., and Mahoney, M. W. Community structure in large networks: Natural cluster sizes and the absence of large well-defined clusters. *CoRR abs/0810.1355* (2008).

[19] LIBEN-NOWELL, D., NOVAK, J., KUMAR, R., RAGHAVAN, P., AND TOMKINS, A. Geographic routing in social networks. *Proceedings of the National Academy of Sciences 102*, 33 (Aug. 2005).

[20] MITZENMACHER, M. A brief history of generative models for power law and lognormal distributions. *Internet Mathematics 1*, 226–251.

[21] OH, J., SUSARLA, A., AND TAN, Y. Examining the diffusion of user-generated content in online social networks. *SSRN eLibrary* (2008).

[22] PAXSON, V. Fast, approximate synthesis of fractional gaussian noise for generating self-similar network traffic. *CoRR cs.NI/9809030* (1998).

[23] PAXSON, V., AND FLOYD, S. Wide area traffic: the failure of poisson modeling. *IEEE/ACM Trans. Netw. 3*, 3 (1995).

[24] PUJOL, J., SIGANOS, G., ERRAMILLI, V., AND RODRIGUEZ, P. Scaling online social networks without pains. In *Proc. of NetDB'09).*

[25] PUJOL, J. M., ERRAMILLI, V., AND RODRIGUEZ, P. Divide and conquer: Partitioning online social networks. http://www.citebase.org/abstract?id=oai:arXiv.org:0905.4918, 2009.

[26] ROUGHAN, M., GREENBERG, A., KALMANEK, C., RUMSEWICZ, M., YATES, J., AND ZHANG, Y. Experience in measuring internet backbone traffic variability: Models, metrics, measurements and meaning. In *Proc. of ITC'03* (2003).

[27] SCHNEIDER, F., FELDMANN, A., KRISHNAMURTHY, B., AND WILLINGER, W. Understanding online social network usage from a network perspective. In *Proc of ACM IMC '09.*

[28] STOUFFER, D. B., MALMGREN, R. D., AND AMARAL, L. A. N. Log-normal statistics in e-mail communication patterns. http://www.citebase.org/abstract?id=oai:arXiv.org:physics/0605027, 2006.

[29] STUTZBACH, D., REJAIE, R., DUFFIELD, N., SEN, S., AND WILLINGER, W. On unbiased sampling for unstructured peer-to-peer networks. *IEEE/ACM Trans. Netw. 17*, 2 (2009), 377–390.

[30] VALAFAR, M., REJAIE, R., AND WILLINGER, W. Beyond friendship graphs: A study of user interactions in flickr. In *WOSN '09.*

[31] VISWANATH, B., MISLOVE, A., CHA, M., AND GUMMADI, K. P. On the evolution of user interaction in facebook. In *Proc. of the 2nd ACM SIGCOMM WOSN'09.*

[32] Weaver, E. Twitter data scheme. http://blog.evanweaver.com/articles/2009/07/06/up-and-running-with-cassandra/.

[33] Wilson, C., Boe, B., Sala, A., Puttaswamy, K. P., and Zhao, B. Y. User interactions in social networks and their implications. In *Proc of EuroSys '09* (2009).